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Three Stage Scheduling of Steel Making using Earliest Deadline First Algorithm

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Abstract: In this paper the authors have ventured into scheduling of Steel Making process from LD converters to Continuous casters including Argon Rinsing stations using Earliest Dead line First (EDF) scheduling algorithms. The authors have evaluated performance metrics of the model like Turnaround time, Average waiting time and Total dead line deviation. The results of EDF scheduling is compared with First Cum First Scheduling (FCFS) , Shortest Job First(SF) scheduling and the results of EDF scheduling has shown better performance over the other two.

Key Words : EDF, Steel Making, Three Stage Scheduling

I. INTRODUCTION:

The steel making and continuous casting system(SCCS) is the bottleneck in the Iron and Steel Production, SCCS often involves various uncertainties such as the emergency customer orders, inaccurate estimate of ingredient components, the unpredictable machine break down or the inaccurate estimate of processing time. How to consider such uncertainties to build a better schedule in a limited time by a computationally efficient manner is becoming critical for the production of iron and steel.

Even slight improvement of production and effective utilization of equipment will leverage and improve the bottom line of the organization. Effective scheduling of heats in LD converter , ARS stations and Continuous casting machines will improve the achievement of the desired/ aim grades of steel and reduce the diversions thereby improving productivity and profitability. The scheduling at different stations aims to reduce the total elapsed time and minimize the average waiting time in each station. The scheduling of jobs at each station LD converters, ARS stations and Continuous casting machines is sequencing of jobs based on the grades of steel to be produced and the time each job spends at each station.

Production planning and scheduling in steelmaking-continuous casting (SCC) process consists of decision making about three important issues: Consolidating customer orders into charges, grouping charges into heats , scheduling the heats on to LD Converters and optimizing the order of the sequences where a sequence is a group of heats with the same chemical characteristics i.e grade of the steel. The job that are processed in LD converters are called Heats and that is assigned heat number. Customer orders are directed from Steel Melting shop. The different grades and their tonnage is decided by customer orders received. The Monthly plan is divided into daily plan which is each grade of steel and tonnage to be produced in a sequence and this is call steel order. The steel order is known well in advance. The steel order is processed in First cum first Basis without any logic. The heats are processed in a sequence in LD Converters, Argon Rinsin stations and continuous casting machines. In this research, the authors have focused on developing different scheduling algorithms to sequence the heats in different stations LD Converters, ARS and CCMS , so that Production , Productivity of the steel by reducing the waiting time in each machine and increasing the utilization of the machines.

The authors Developed Earliest Deadline First (EDF) scheduling with different functions for the scheduling of Steel Melting and Continuous Casting Shop scheduling to improve productivity and thereby cost of production. The metrics like turnaround time, average waiting time and Total deadline deviation which are used to evaluate performance of the scheduling algorithms are computed for the EDF and these are compared with Shortest Job First (SJF), First Cum First Scheduling. The metrics are computed on the heats from the steel plant production data.

These results indicated that the EDF scheduling model has shown a significant improvement of over First Come First Scheduling (FCFS) , Short Test Job First (SJF). This indicated that in the steel making the model EDF has given effective utilization of LD Converters, Argon rinsing stations , Continuous Casting Machines and improvement of productivity over presently being used FCFS modeling.

II. RELATED WORK

Liro Harunkoski, Guido Sand et.al [2008], discussed Mixed-Integer Linear Programming (MILP) models for meltshop scheduling optimization that can be flexibly adapted to different plant structures. Moreover, the flexibility allows for modeling individual characteristics of parallel equipment, particular processing and changeover times, scarce resources and maintenance requests. Kebin Lu, Kewei Huang et.al. ,[2008], have developed a hybrid heuristic and optimisation algorithm is

developed for integrated scheduling problem of steel-making and continuous casting. The scheduling system had been embedded into the MES system of Iron and steel plant of China. Satisfactory results have been achieved.

Arezoo Atighehchian, Mehdi Bijari et.al.,[2009], have proposed algorithm for scheduling Steel Making and Continuous casting named HANO, is based on combination ant colony optimization and non-linear optimisation methods. The efficiency of HANO is compared with heuristic algorithms. Numerical results reveal the higher efficiency of the proposed approach compared with heuristic approach. Hubert Missbauer et al (2009), presented the models, algorithms and implementation results of a computerized scheduling system for the steelmaking-continuous casting process of a steel plant in Austria. Extensive numerical tests with real-life data and more than two years of experience with the implementation demonstrate that the system produces reasonable schedules and is accepted by the planners.

Xiu-ying wang etal (2010) , presented a model for scheduling steel-making and continuous casting combining the mathematical programming, fuzzy logic, expert system based techniques. The results demonstrated that the proposed scheduling strategy to some extent satisfy the requirement of practical production. Lianglinag Sun, Wei Liu, Perter B Luh et.al. [2011], adopted stochastic dynamic programming for solving the Steel Making-Continuous casting scheduling problem. The model is relaxed by lagrangian relaxation multipliers a good dual solution is selected by using ordinal optimization. The method has been tested by using practical data from the shanghai Bashan Steel Plant in China and could get near optimal solutions in a limited time.

Li dqwei, Shang Ranran et.al. [2012] , presented co-ordination grouping ant colony model to solve the steel making, Continuous casting and hot charging of rolling mills scheduling . The model is validated with practical production data and found that the algorithm developed is feasible and effective for the batch scheduling problem. Bai-linwang,tie-ke et.al. [2013], they have represented the constraints and dynamic scheduling of steel making and continuous casting by hybrid knowledge with frames and production rules. They have solved the dynamic scheduling by a tree hierarchy architecture and real time rule based reasoning dynamic scheduling strategy is implemented by inference mechanism.

Maria Pia Fanti, Giuliana Rotunno et.al [2013], proposed mixed integer linear programming formulation for minimizing the maximum completion time and the scheduling of the continuous casting machines. The authors enlightened how a proper scheduling of the Steel Making and Continuous casting is of basic importance to obtain good system performances. Sun Liang-liang, WANG Xiu-Ying [2013], proposed an optimal scheduling method for Steel Making , Continuous Casting which consisted of equipment assignment algorithm based on dynamic program technique and conflict elimination algorithm based on linear program technique. Numeric results demonstrate solution quality, computational efficiency, and values of the models and algorithm.

Steven Gay, Pierre Schaus et.al. [2014], they have presented a constraint programming (CP) model related scheduling of operations for steel making with continuous casting. The activities considered range from the extraction of iron in the furnace to its casting in the continuous casters. Kiatkajohn Worapradya, Purit Thanakijkasem ,[2015], have proposed an effective proactive scheduling that utilizes robustness adopting a distribution curve of a system performance created as a mix-integer model with artificial neural network(ANN) for scheduling Steel Making and Continuous Casting . The ANN model is achieved by applying k-mean clustering, which decomposes machine to smaller groups having similar effect to the uncertainty. The experimental result shows that the methodology is successful in designing a robust schedule that provides a lower cost of production.

Ling Li, Qiuhua Tang, Peng Zheng et.al. [2016] , proposed a novel improved self-adaptive genetic algorithm to optimize the scheduling sequence of steel making -continuous casting casts with the objective of reducing the total idle times on all machines and minimizing the make-span. Experimental comparisons with GAMS/CPLEX and other two state-of-art algorithms demonstrate the effectiveness and efficiency of SAGA in solving the large-size problems. AchrafTouil, Abdelwahed Echchtabi, [2016], proposed a hybrid meta heuristic algorithm to maximize the production and to minimize the processing time in the steel-making and continuous casting (SCC) by optimizing the order of the sequences where a sequence is a group of jobs with the same chemical characteristics. After parameter tuning of the proposed algorithm, it is tested on different instances using a.NET application and the commercial software solver Cplex v12.5. These results are compared with those obtained by SA-TL. Mohammad Reza Yadollahpour, et.al. [2016], presented heuristic algorithm for steel making – continuous casting scheduling to consolidate steel orders into charges and group charges into continuous casting casts. This method has been successfully used for Mobarakeh steel company , the biggest steel enterprise in the middle east computational experiments demonstrate that the proposed method substantially increase the productivity in MSC.

In the literature, very little work on Scheduling of Steel Making and Continuous Casting (SCC) reported. In the available literature researchers have focused on genetic algorithms, heuristics, linear programming and Nueral networks to solve the Steel Making and Continuous Casting (SCC) scheduling problem. Due to dynamism of machines involved in Steel making , no scheduling model is perfectly models the scheduling problem. Lot of research is still going on to find best algorithms for SCC scheduling by using different mechanisms. No author reported the research on SCC Scheduling using Earliest Deadline Concept. Deadline aware Scheduling concept is most important concept being used in all industrial scheduling activities. Hence authors have chosen EDF methodology for scheduling of heats

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to LD converters, ARS stations and continuous casting of steel making.

III. THREE STAGE SCHEDULING OF STEEL MAKING USING EARLIEST DEADLINE FIRST ALGORITHM:

The scheduling of Steel Making and Continuous Casting involves sequencing of heats based on the grade to be made and timings in each unit to be spent. Deriving an optimized sequencing of the Heats/Jobs from converter to Caster will give more productivity and optimum machine utilization. The aim of the research is to derive an optimized scheduling based on the timings of blow, rinsing and casting which is depends on the many metallurgical constraints.

In this paper authors have considered three units of steel making namely LD Converter, Argon Rinsing Unit and continuous casting machines. In this research it is considered that there are 'm' number of converters, 'n' number of Argon Rinsing Units and 'o' number of Continuous Casting Machines parallely processing heats. The model randomly determines a factor for each job/heat and finds out a deadline time for each job/heat. After deadlines are arrived for each heat / job the jobs are ordered based on the deadline function in ascending order is arranged. The scheduling model considers for each 4 jobs/heats it sequences on one stream of LD converter (M1), Argon Rinsing Station (M2) and Continuous Casting Machines (M3). The concept of multiple machine scheduling is depicted in Figure 3.1.

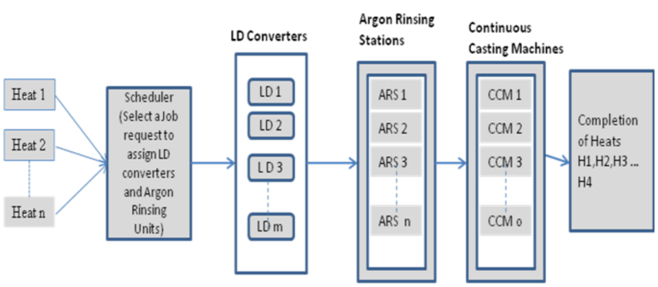

Fig: 3.1

Deadline time for each job/heat is calculated based on the total time it takes to process each heat in the LD converter (M1), Argon Rinsing Station (M2) and Continuous Casting Machines (M3) and multiplied with random number α. The deadline function is defined as $\beta * (M_1+M_2+M_3) + \gamma *$ deadline time where β, γ are factors decided based on the best optimization and $\beta + \gamma = 1$. The schedule sequence is arranged in ascending order as per deadline function value. The ordered sequence is split into 2 sets of sequences and each set shall have 4 jobs/heats. In each set start time, waiting time and deadline variation is computed. If the dead line variation is minimum, that scheduling sequence is declared as best optimized sequence.

IV. METHODOLOGY

In this paper the authors took 8, 256 and 512 jobs with Processing Times on M_1, M_2 and M_3 i.e LD Converter Blowing time (t_{i1}), Argon Rinsing time (t_{i2}) and Continuous Casting Machines (t_{i3}). The deadline time for each job is calculated using function $\alpha*(t_1+t_2+t_3)$ where t_1, t_2 and t_3 are processing times and α is random number varies between 2 and 4. The scheduling at LD converter, ARS stations and CCM Machines is done using EDF methodology on the data presented in Table:4.1 and it is compared with FCFS and SJF. Various Performance metrics like Average Elapsed Time (AET) and total deadline violations is computed and compared. Java simulation programme is developed to compute all scheduling methods. Out of 8 jobs, it is considered that each 4 jobs/heats will run on one stream of machines M_1, M_2 and M_3 accordingly the computations are done. So that starting times after four jobs / heats will become zero for the first job/heat in that stream.

Job id	M1	M2	M3	DLi	Alpha
0	15	20	107	284	2
1	16	13	85	456	4
2	16	17	104	205	1.5
3	19	22	88	516	4
4	19	13	114	219	1.5
5	18	26	87	655	5
6	17	29	122	420	2.5
7	17	18	111	438	3

Table 4.1: Eight Jobs with processing timings on each m/c

Waiting Time of a job request is the time elapsed between the arrival time of job request and when the job request starts its work on Machine of type-1, plus the time elapsed between the time it completes its work on Machine of type-1 and starts its work on Machine of type-2, plus the time elapsed between the time it completes its work on Machine of type-2 and starts its work on Machine of type-3. The Total Elapsed Time of the entire schedule is the time when all job requests completed their work on both machines of type-1, type-2 and type-3 respectively. Total Elapsed time of this schedule is the c_k, where k is the last request in the schedule given by the scheduling algorithm. The performance metrics can be computed by the following computations for a given scheduling sequence. Average Elapsed Time (AET) of the schedule can be computed as follows.

$$AET = \sum_{i=0}^{p} \text{Completion Time of Schedule Seqi}$$

$$TDV = \sum_{i=0}^{n} DLi - Ci \text{ where } C_i > DL_i$$

n : Number of jobs.
I : Job Request Number
t_{i1} : The time required on Machine of type-1 (M_1) for job request i.
t_{i2} : The time required on Machine of type-2 (M_2) for job request i.
t_{i3} : The time required on Machine of type-3 (M_3) for job request i.
c_i : Completion time of job request i Machine of type-3.
Seq_i : Sub Scheduling Sequence Seq_i

V. ANALYSIS AND COMPARISON OF RESULTS

Using the Java simulation programming the FCFS, SJF and EDF scheduling results computed and the results are tabulated below.

FCFS Scheduling Results:

Eight jobs/Heats of different grades are scheduled on First Cum First Basis and there are scheduled on LD Converters First (M1), Argon Rinsing Units (M2) and Continuous Casting Machines (M3) . The start time of Job/ Heat on M1, M2, Finish time of job on M3, Waiting Time (WT) and dead line and dead line violation is computed using computer programming as per the formulas mentioned above. In the set of heats below every four heats are scheduled on one set of M1,M2 and M3 . Total 2 LD converters ,2 Argon Rinsing units and 2 Continuous casting machines are used and parelley processing the heats. The elapsed time for each set of machines processing calculated. The results are shown in Table 5.1.

Job id	Start Time	Completion Time	Waiting Time	Deadline DL_i	DeadLine Violation
0	0	142	0	284	0
1	15	227	113	456	0
2	31	331	194	205	126
3	47	419	290	516	0
4	0	146	0	219	0
5	19	233	102	655	0
6	37	355	187	420	0
7	54	466	320	438	28

Table 5.1: FCFS Scheduling Computation Results

SJF Scheduling Results:

In this jobs/ heats are arranged in the order of Shortest Job i.e. total time of processing on LD Converters (M1), Argon Rinsing Units (M2) and Continuous casting Machine (M3) together. After arranging the heats in Shortest Job First basis, each set of four heats are processed on one set of M1 , M2 and M3. The Start Time, Finish Time, Waiting Time, dead line and dead line violation is computed for each heat and shown in Table 5.2.

Job id	Start Time	Completion Time	Waiting Time	Deadline DL_i	DeadLine Violation
0	34	308	166	284	24
1	0	114	0	456	0
2	19	233	96	205	28
3	0	129	0	516	0
4	49	422	276	219	203
5	16	201	70	655	0
6	52	466	298	420	46
7	35	344	198	438	0

Table 5.2: SJF Scheduling Computation Results

EDF Scheduling Results:

The model randomly determines a factor for each job/heat and finds out a *deadline time* for each job/heat. After deadlines are arrived for each heat / job the jobs are ordered based on the *deadline function* in ascending order is sequenced. The scheduling model considers for each 4 jobs/heats it sequences on one stream of LD converter (M1) Argon rinsing station (M2) and continuous casting Machine (M3). The start time of Job on M1, Finish Time of Job on M3, Wait Time , Dead Line and Dead Line Violation is computed for each Job ID / Heat Id and tabulated in Table 5.3. The Dead Line Time (DLT) is computed with (M1 + M2 + M3) Alpha and Alpha is a random value between 2 to 4. The Dead Line Function is computed based on the formula β * DLT + γ * (M1 + M2 + M3). Where Beta and Gamma are chosen randomly such that Beta + Gamma = 1.In this research β is taken as 0.2 and γ is taken as 0.8. Based on the Dead Line Function the sequence is ordered in ascending form. The dead line variation is difference between dead line and finish time of job on M3. If it is negative the dead line violation is zero otherwise it is same positive value. This indicates that the job/heat is completed within the dead line time then there is dead line violation.

Job id	Start Time	Completion Time	Waiting Time	Deadline DL_i	DeadLine Violation
0	16	244	102	284	0
1	19	231	117	456	0
2	0	137	0	205	0
3	35	319	190	516	0
4	0	146	0	219	0
5	54	406	275	655	0
6	48	477	309	420	57
7	31	355	209	438	0

Table 5.3: EDF Scheduling Computation Results

The Scheduling sub sequences and its elapsed times of FCFS, SJF and EDF are shown in the Table 5.4.

Scheduling Model	Scheduling Sequence	Seq_i	Elapsed Time
FCFS	0..1..2..3..	1	419
FCFS	4..5..6..7..	2	466
SJF	1..5..0..4..	1	422
SJF	3..2..7..6..	2	466
EDF	2..0..7..6..	1	477
EDF	4..1..3..5..	2	406

Table 5.4: Scheduling Sub Sequences and Elapsed Times

Comparison of Results:

Java simulation programme is developed for computation of average waiting time and deadline violation. In the table 5.1 eight jobs are listed with M1, M2, M3 timings. The deadline time is calculated based on the (M1+M2+M3) timings and alpha is randomly chosen between 2 to 4.

The Average Elapsed Time, Total Dead Line Violation of the EDF scheduling model when compared with FCFS and SJF is shown in Table 5.5. The graphical comparison of Scheduling Model and Average Elapsed Time and total dead line violation is shown in Figure 2. The graphical Comparison of Scheduling model and Total Dead line Violation is shown in Figure 5.1. These values indicates that EDF (441.5) scheduling model is comparable with FCFS (442.5) and SJF (444) in terms of Average Elapsed Time . The total deadline violation values indicates that the EDF (37) scheduling is giving much better results when compared with SJF (301) and FCFS (154).

Scheduling Model	Average Elapsed Time	Total Deadline Violation
FCFS	442.5	154
SJF	444	301
EDF (3 Stage)	441.5	57

Table 5.5 Scheduling Model vs AET & TDV (n=8, p-2)

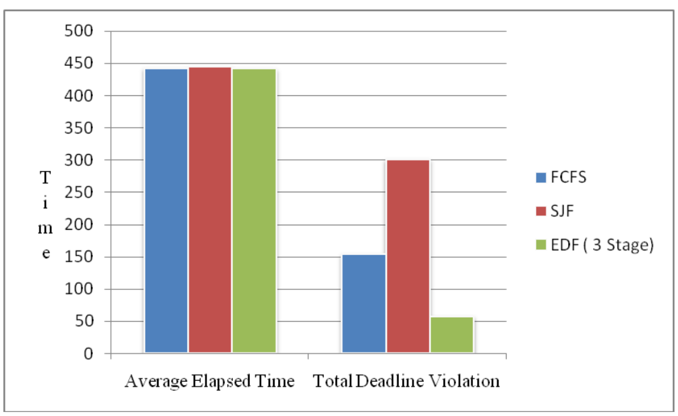

Figure 5.1 : Depicting AET, TDV for each Algorithm

Similarly the authors have computed Average elapsed time, total deadline violation for FCFS,SJF, EDF for n=256 and p=64 and the results are tabulated in Table 5.6.

Scheduling Model	Average Elapsed Time	Total Deadline Violation
FCFS	455	11022
SJF	453	10873
EDF (3 Stage)	453	1231

Table 5.6 Scheduling Model vs AET & TDV (n=256, p-64)

The graphical comparison of Scheduling Model and Average Elapsed Time and total dead line violation is shown in Figure 5.2.

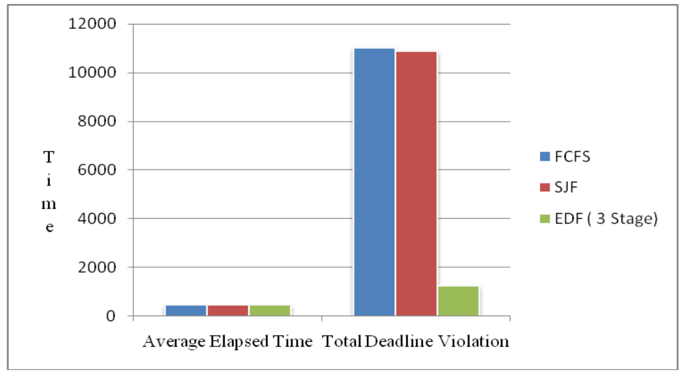

Figure 5.2: Depicting AET,TDV for each algorithm

VI. Conclusion

In this research EDF model is used for scheduling the heats at LD converter, ARS Stations and continuous casting machines. The scheduling results are compared with other conventional models viz FCFS and SJF. The result shows that EDF Model performance in terms of total deadline violation is much better than other FCFS and SJF, this implies that the deviation from deadline time is much less and better than others. The average elapsed time for a job in the case of EDF is comparable with FCFS and SJF.

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